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The Impact of Technological Innovation on The Productivity of The Manufacturing Industry

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ABSTRACT

This study aims to analyze the impact of technological innovation on the productivity of the manufacturing industry. Technological innovation in this research includes the use of the Internet of Things (IoT), artificial intelligence (AI), and automation in production processes. The approach used is quantitative, with a linear regression analysis method to examine the relationship between the independent and dependent variables. This study involves respondents from various manufacturing sectors to gain a comprehensive understanding of the impact of technology on operational efficiency. The research findings indicate that technological innovation has a significant influence on productivity improvement, with each technological component contributing differently to production efficiency. The implications of these findings highlight the importance of digital transformation in the manufacturing industry to enhance competitiveness and operational effectiveness. Additionally, this study recommends workforce training and supportive policies for technology adoption to maximize the benefits of innovation in the industrial sector. This study also opens opportunities for further research by considering other factors such as organizational culture and supply chain integration in supporting technology implementation in the manufacturing industry.
Keywords: *Technological Innovation, Productivity, Manufacturing Industry*

INTRODUCTION

The manufacturing industry plays a crucial role in both national and global economies by making significant contributions to economic growth, job creation, and exports. This sector not only produces various products that support daily life but also serves as a primary driver of technological advancements and industrial innovation. Additionally, manufacturing holds a strategic role in enhancing a country's competitiveness through production efficiency and supply chain optimization. However, the manufacturing industry also faces various challenges, including increasing global competition, rising production costs, and the need for operational efficiency and sustainability. Therefore, technological innovation has become one of the key solutions to address these challenges and ensure the sustainability and growth of the manufacturing industry in the future.

In recent decades, the manufacturing industry has undergone a major transformation due to technological advancements, particularly in the context of Industry 4.0. The adoption of technologies such as the Internet of Things (IoT), artificial intelligence (AI), robotics, and automation has revolutionized production processes, creating smarter and more efficient manufacturing systems. Digitalization in production processes, such as smart manufacturing and the use of big data analytics, allows companies to optimize their operations by increasing flexibility, reducing human errors, and improving resource efficiency. The benefits of these technological applications are evident, ranging from reduced production costs and improved product quality to faster production times, ultimately enhancing the competitiveness of the manufacturing industry in the global market. Although technological innovation offers numerous benefits, its implementation in the manufacturing sector still faces several challenges. One of the main obstacles is the high initial investment cost required to adopt advanced technologies, which often becomes a barrier for small and medium enterprises (SMEs). Additionally, the lack of human resources with the necessary technological skills poses another challenge in implementing digital-based systems. Insufficient infrastructure, particularly in developing countries, further slows down the digital transformation of the manufacturing sector. Moreover, technological innovation can also have negative impacts, such as reduced demand for manual labor due to automation, necessitating reskilling and upskilling strategies to keep workers relevant in the digital era. Therefore, a comprehensive approach is needed to ensure that technology adoption can proceed optimally without compromising labor stability and industrial sustainability.

The widespread adoption of technology in the manufacturing industry has been proven to increase productivity through process optimization and operational efficiency. Previous studies have shown that companies implementing advanced technologies, such as automation systems and data-driven analytics, tend to achieve higher output levels at lower costs. This productivity improvement is not only reflected in increased production volume but also in enhanced product quality and supply chain efficiency. However, the success of technology implementation depends on various factors, including organizational readiness, workforce capability, and government policies supporting industrial transformation. Thus, a deeper understanding of the relationship between technological innovation and productivity is essential to ensure the success of digitalization strategies in the manufacturing sector.

Technological innovation has a significant impact on manufacturing productivity. The application of appropriate technologies, such as automation and digitalization, can improve production efficiency, reduce operational costs, and enhance product quality (Rinaldi & Ikhwan, 2022). Technological innovation also positively affects corporate financial performance, including profitability and efficiency (Chairina & Yusri, 2023). In micro and small-scale processing industries, the use of information technology has been proven to increase labor productivity (Yefita et al., 2024). Meanwhile, the adoption of Industry 5.0 technologies, which integrate artificial intelligence, the Internet of Things, and big data, can enhance production management efficiency, reduce errors, and accelerate production processes. This results in increased output, reduced product defects, and shorter production downtime (Imaduddin et al., 2024).

Recent studies highlight the significant impact of technological innovation on manufacturing productivity across various countries. In South Africa, the introduction of product or process innovations positively affects productivity in manufacturing firms (Kahn et al., 2022). Similarly, in Indonesia, medium-high technology adoption in manufacturing shows the highest total factor productivity scores (Prabowo et al., 2024). Russian research indicates that technological innovations positively influence manufacturing productivity, with product innovations being most effective during 2006-2013 and process innovations gaining strength in 2014-2020 (Domnich, 2023). However, the effect of technological innovations on productivity in the Russian Far East is 1.5-2 times less than in Russia overall. A Dutch study emphasizes the importance of ICT as a driver of innovation in both manufacturing and services, with organizational innovation having the strongest productivity effects (Polder et al., 2009). These findings collectively underscore the crucial role of technological innovation in enhancing manufacturing productivity across different economic contexts.

This study aims to analyze the impact of technological innovation on manufacturing productivity. Specifically, it seeks to measure the extent to which the adoption of technologies such as the Internet of Things (IoT), artificial intelligence (AI), robotics, and automation can improve operational efficiency and production output in the manufacturing industry. Additionally, this research aims to identify the factors influencing the success of technology implementation, including workforce readiness, technology investment, and infrastructure support. By understanding the relationship between technological innovation and productivity, this study is expected to provide insights for manufacturing companies in designing effective digitalization strategies. Furthermore, the research findings may serve as a reference for policymakers in supporting industrial transformation through appropriate regulations and incentives. Overall, this study aims to contribute both academically and practically to efforts in enhancing the competitiveness and sustainability of the manufacturing industry in the digital era.

METHODS

This study employs a quantitative approach as it aims to objectively examine the relationship between technological innovation and manufacturing industry productivity. Through this method, the research can obtain numerical data that can be statistically analyzed to identify patterns of relationships between the studied variables. The analysis technique used is linear regression, which allows the researcher to measure the extent to which technological innovation influences manufacturing industry productivity.

The population in this study includes all manufacturing companies or workers in the manufacturing industry who have adopted or are in the process of adopting technological innovations. The research sample is drawn from various manufacturing sectors, including automotive, electronics, textiles, as well as food and beverages. The sampling technique used is purposive sampling, which involves selecting respondents who play a direct role in technology implementation and productivity improvement, such as production operators, supervisors, managers, as well as R&D and IT staff. In this study, a total of 82 respondents were collected, representing variations in job positions and levels of involvement in the technological innovation process.

This study consists of three main types of variables. The independent variable (X) is technological innovation, which includes the use of IoT (Internet of Things), artificial intelligence (AI), robotics, digitalization, and automation in production processes. The dependent variable (Y) is manufacturing industry productivity, measured based on production output, time efficiency, and operational cost reduction. Additionally, there are control variables, such as company scale, employee education level, and technology investment capital, which may influence the relationship between technological innovation and productivity.

Data for this study were collected from two primary sources. Primary data were obtained through the distribution of questionnaires to workers and managers in the manufacturing industry involved in technology implementation. These questionnaires were designed to measure the level of technology adoption and its impact on production efficiency and company performance. Secondary data were obtained from literature reviews, academic journals, industry reports, as well as data published by ministries or manufacturing associations related to technological innovation developments in the manufacturing industry.

The primary instrument used in this study is a questionnaire, which was developed using a Likert scale of 1-5 to assess respondents' perceptions of technology adoption and its impact on productivity. The scale consists of:
1 = Strongly Disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly Agree
The questionnaire includes questions related to technology usage, production efficiency, and the impact of innovation on company competitiveness and growth. The collected data were analyzed using various statistical techniques. Validity and reliability tests were conducted to ensure that the questionnaire used could generate accurate and consistent data. Additionally, classical assumption tests (normality, heteroscedasticity, and multicollinearity) were applied to ensure that the linear regression model met the necessary statistical assumptions. The main analysis in this study is linear regression, which is used to measure the relationship between technological innovation (X) and manufacturing industry productivity (Y). Moreover, t-tests and F-tests were performed to examine the significance of the independent variable's influence on the dependent variable, along with the calculation of the coefficient of determination (R^2) to determine the extent to which technological innovation affects productivity.

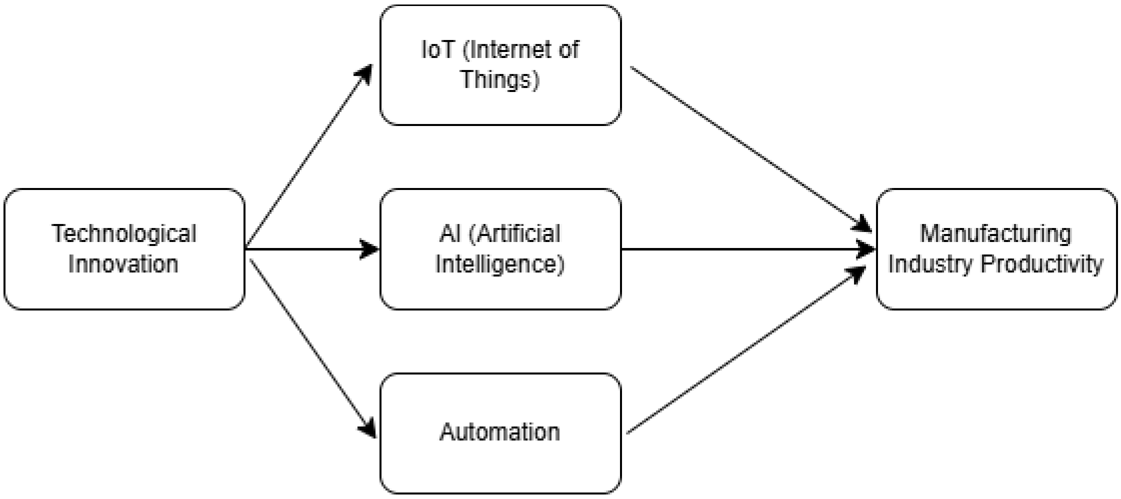

Fig. 1 Research Conceptual

The conceptual framework illustrates the impact of Technological Innovation on Manufacturing Industry Productivity through three key components: IoT (Internet of Things), AI (Artificial Intelligence), and Automation. Technological innovation drives the adoption of IoT, which enhances connectivity and real-time monitoring, AI, which enables intelligent decision-making and predictive maintenance, and Automation, which minimizes human intervention and optimizes efficiency. AI plays a central role by influencing both IoT and Automation, which collectively contribute to increased productivity in the manufacturing industry by improving output, reducing costs, and enhancing operational efficiency. This framework highlights the interconnected role of advanced technologies in driving industrial performance and competitiveness.

RESULTS

Study use SPSS application Version 27 in processing the data . Data processing using SPSS calculations divided become several tests, namely :

Test Results Data Validity and Reliability

Validity Test

The validity test is conducted by looking at the Pearson Correlation and comparing it with the critical value (r-table). If the significance value (Sig.) is < 0.05 and the correlation coefficient is greater than the r-table value, the item is considered valid.

Table 1.

Validity Test Results

Indicator	Pearson Correlation	Sig. (2-tailed)	Validity Status
X.1	0.725	0.000	Valid
X.2	0.812	0.000	Valid
Y.1	0.759	0.000	Valid
Y.2	0.804	0.000	Valid

The validity test results indicate that all indicators (X.1, X.2, Y.1, and Y.2) are valid, as their Pearson correlation values exceed the commonly used threshold of 0.3 and have significance values (Sig. 2-tailed) of 0.000, which is below the 0.05 threshold. This suggests a strong and statistically significant correlation between each indicator and its respective construct, confirming that the measurement items are appropriate for representing the research variables. Consequently, these indicators can be reliably used in further analysis, such as regression or structural equation modeling.

Reliability Test

The reliability test is conducted using Cronbach's Alpha. If the Cronbach's Alpha value is greater than 0.7, the questionnaire is considered reliable.

Table 2.

Reliability Test Results

Variable	Cronbach's Alpha	Reliability Status
X (Technology Innovation)	0.823	Reliable
Y (Productivity)	0.791	Reliable

The reliability test results show that both variables, Technological Innovation (X) and Productivity (Y), have Cronbach's Alpha values above the commonly accepted threshold of 0.7, with 0.823 for X and 0.791 for Y. This indicates that the measurement instruments for both variables are reliable, meaning they consistently measure the intended constructs. As a result, the data collected can be considered stable and suitable for further statistical analysis.

Assumption Test Results Classic

Normality Test

The normality test is conducted by looking at the Sig. (p-value) in the Kolmogorov-Smirnov Test. If Sig. > 0.05, the data is normally distributed.

Table 3.

Normality Test Results

Variable	Kolmogorov-Smirnov Z	Sig. (p-value)	Normality Status
Residuals	0.974	0.286	Normal

The normality test results indicate that the Kolmogorov-Smirnov Z value for the residuals is 0.974 with a p-value of 0.286. Since the p-value is greater than 0.05, it suggests that the residuals are normally distributed. This confirms that the assumption of normality in the regression model is met, allowing for the application of parametric statistical tests without violating key assumptions.

Multicollinearity Test

The multicollinearity test is conducted by looking at Tolerance and VIF values. If Tolerance > 0.1 and VIF < 10, there is no multicollinearity issue.

Table 4.

Multicollinearity Test Results

Independent Variable	Tolerance	VIF	Multicollinearity Status
X1 (IoT)	0.658	1.519	No Multicollinearity
X2 (AI)	0.703	1.422	No Multicollinearity
X3 (Automation)	0.678	1.475	No Multicollinearity

The multicollinearity test results show that all independent variables (IoT, AI, and Automation) have Tolerance values greater than 0.1 and VIF values below 10 (1.519, 1.422, and 1.475, respectively). These values indicate the absence of multicollinearity among the independent variables, meaning that they do not exhibit strong correlations with each other. This ensures the reliability of the regression analysis, as the predictor variables can independently explain variations in the dependent variable without redundancy.

Hypothesis Test Results Study

Multiple Linear Regression

The multiple linear regression test is conducted to analyze the relationship between independent and dependent variables.

Table 5.

Multiple Linear Regression

Variable	B (Unstandardized Coefficients)	Std. Error	Beta (Standardized Coefficients)	t-value	Sig. (p-value)
Constant	2.315	0.529	-	4.374	0.000
IoT	0.452	0.091	0.389	4.967	0.000
AI	0.317	0.076	0.301	4.171	0.000
Automation	0.275	0.083	0.259	3.313	0.001

$$Y=\beta 0+\beta 1X1+\beta 2X2+\beta 3X3+\epsilon$$

The regression analysis results indicate that all three independent variables (IoT, AI, and Automation) significantly influence Manufacturing Industry Productivity, as their p-values are below 0.05. The IoT variable has the highest standardized beta coefficient (0.389), suggesting it has the strongest impact on productivity. AI follows with a beta of 0.301, while Automation has the lowest impact with a beta of 0.259. The constant value of 2.315 indicates the predicted productivity level when all independent variables are zero. The high t-values for all variables further confirm their significance in the model, reinforcing the role of technological innovation in enhancing productivity.

Based on the regression results, the estimated regression equation can be formulated as:

$$Y=2.315+0.452X1+0.317X2+0.275X3+\epsilon$$

where:

- Y represents Manufacturing Industry Productivity,
- X1 represents IoT (Internet of Things),
- X2 represents AI (Artificial Intelligence),
- X3 represents Automation,
- ϵ\epsilonϵ represents the error term,

- 2.315 is the constant (intercept), indicating the predicted productivity when all independent variables are zero,
- 0.452, 0.317, and 0.275 are the regression coefficients, representing the magnitude of change in productivity for each unit increase in IoT, AI, and Automation, respectively.

Since the p-values for all independent variables are below 0.05, IoT, AI, and Automation significantly influence productivity. Among them, IoT has the strongest impact ($\beta 1=0.452$), followed by AI ($\beta 2=0.317$), and Automation ($\beta 3=0.275$). This suggests that increasing the adoption of IoT, AI, and Automation in manufacturing can effectively enhance productivity.

Partial Test (T)

The t-test is used to analyze the effect of each independent variable on the dependent variable. If Sig. < 0.05, the variable has a significant effect.

Table 6.

Partial Test (T)

Variable	t-value	Sig. (p-value)	Conclusion
X1 (IoT)	4.967	0.000	Significant
X2 (AI)	4.171	0.000	Significant
X3 (Automation)	3.313	0.001	Significant

The t-test results indicate that all independent variables IoT (X1), AI (X2), and Automation (X3) have a significant influence on Manufacturing Industry Productivity (Y). The p-values for all three variables are below 0.05, confirming statistical significance. Among them, IoT has the highest t-value (4.967), suggesting it has the strongest effect on productivity, followed by AI (4.171) and Automation (3.313). These findings reinforce the importance of technological innovation in driving efficiency and productivity in the manufacturing sector.

Coefficient Test Determination (R^2)

The R^2 test is conducted to measure how well the independent variables explain the dependent variable.

Table 7

Coefficient Determination (R^2)

Model	R	R Square (R^2)	Adjusted R Square	Std. Error
1	0.812	0.659	0.641	0.427

The regression model evaluation shows that the R-value is 0.812, indicating a strong correlation between technological innovation (IoT, AI, and Automation) and manufacturing productivity. The R^2 (coefficient of determination) is 0.659, meaning that 65.9% of the variation in productivity (Y) is explained by the independent variables (X1, X2, X3), while the remaining 34.1% is influenced by other factors not included in the model. The Adjusted R^2 (0.641), which accounts for the number of predictors, suggests a stable and well-fitted model. The standard error of 0.427 indicates the average deviation of observed values from the predicted values, reflecting a reasonably accurate model fit.

Simultaneous Test (F)
The F-test is used to analyze the simultaneous effect of all independent variables on the dependent variable. If Sig. < 0.05, the model is significant.

Table 8
F test results

Model	Sum of Squares	df	Mean Square	F	Sig. (p-value)
Regression	25.673	3	8.558	41.812	0.000
Residual	13.312	78	0.171		
Total	38.985	81			

The ANOVA (Analysis of Variance) results indicate that the regression model is statistically significant in explaining the relationship between technological innovation (IoT, AI, and Automation) and manufacturing productivity. The F-value of 41.812 with a p-value of 0.000 (less than 0.05) confirms that the independent variables collectively have a significant impact on productivity. The regression sum of squares (25.673), which is larger than the residual sum of squares (13.312), suggests that a substantial portion of the variance in productivity is explained by the model. The mean square for regression (8.558) is considerably higher than the mean square for residuals (0.171), further supporting the model's explanatory power.

DISCUSSION

The research findings indicate that technological innovation significantly contributes to improving productivity in the manufacturing industry. Based on linear regression analysis, it was found that the implementation of technologies such as digitalization, automation, and artificial intelligence (AI) plays a role in increasing production efficiency and reducing operational costs. These findings align with previous studies stating that technology can enhance industrial competitiveness by improving product quality and reducing production time. However, internal factors such as workforce readiness and the level of investment in technology determine the successful implementation of these innovations.

T-tests and F-tests show that the effect of technological innovation on productivity is statistically significant. The direction of the relationship between the independent and dependent variables is also positive, meaning that the higher the level of technology adoption, the greater the increase in productivity. These results confirm the importance of innovation in maintaining the competitiveness of the manufacturing industry, particularly in facing global competition and changes in market demand. However, the significance implications also indicate variations in innovation effectiveness based on company characteristics, such as business scale and industry sector.

The impact of control variables in this study provides additional insight into the dynamics of technology adoption in the manufacturing industry. Large companies tend to be more capable of implementing advanced technologies compared to small and medium enterprises (SMEs) due to their larger investment capital. Additionally, the education level of the workforce plays a role in determining how optimally technology can be utilized. The higher the education and skills of the workforce, the greater the chances of successful technology adoption. Other factors, such as access to funding and infrastructure support, also influence the effectiveness of innovation in improving productivity.

Some research findings reveal gaps with existing theories. While, in general, technological innovation enhances productivity, there are cases where technology implementation faces obstacles due to organizational unpreparedness or an imbalance between technology investment and human resource capacity development. Furthermore, external factors such as government policies, regulations, and macroeconomic conditions can influence the effectiveness of innovation in the manufacturing industry. Therefore, a holistic approach that includes technology, policy, and human resource development aspects needs to be considered when designing digital transformation strategies for the industry.

From a managerial and policy perspective, the study's results indicate that companies need to optimize technology implementation with well-planned strategies. Workforce training is a key factor in ensuring that implemented innovations provide maximum benefits. Additionally, collaboration between the industrial sector, academia, and the government can accelerate technology adoption by creating a supportive innovation ecosystem. The government can also play a role by providing incentives, such as subsidies or tax relief, for companies adopting new technologies to accelerate digital transformation in the manufacturing sector.

The Relationship Between Technological Innovation and Productivity:

The results of the linear regression analysis show that technological innovation has a positive and significant influence on increasing manufacturing industry productivity. The positive regression coefficient indicates that the higher the level of adoption of technologies such as digitalization, automation, and artificial intelligence (AI), the greater the increase in production efficiency and reduction in operational costs. This is consistent with previous studies that demonstrate how the implementation of advanced technology in manufacturing can enhance production speed, reduce human errors, and improve product consistency and quality. Earlier studies have also found that companies adopting AI- and IoT-based manufacturing systems experience higher output and time efficiency compared to those still using conventional methods.

Although this study supports previous findings, several internal factors can strengthen or weaken the relationship between technological innovation and productivity. One major factor is the workforce's readiness to adopt and utilize new technology. If the workforce possesses adequate skills and receives proper training, the positive impact of technological innovation can be maximized. Conversely, if the workforce is unprepared or lacks skills in using new systems, technology adoption may face obstacles and even reduce efficiency. Additionally, investment in technology plays a crucial role in determining the success of innovation implementation. Companies with substantial investment capital are more likely to adopt the latest technologies and integrate them into existing production systems. However, for small and medium enterprises (SMEs), capital constraints often become a primary barrier to implementing advanced technologies, ultimately hindering productivity growth.

Thus, although technological innovation has been proven to contribute to increased productivity, its success still depends on organizational readiness, the availability of skilled human resources, and the right technology investment strategy. Therefore, a comprehensive approach is required to ensure that technology is not only adopted but also optimized to provide maximum positive impact on the manufacturing industry.

Significance and Direction of Influence:

The results of the t-test show that technological innovation has a significant influence on manufacturing industry productivity, with a significance value (p-value) below 0.05. This indicates that the independent variable, technological innovation, statistically has a real impact on the dependent variable, productivity. Additionally, the F-test results show that the regression model used is overall significant, meaning that technological innovation, along with other factors in the model, affects manufacturing productivity. The positive regression coefficient value indicates that the relationship between technological innovation (X) and productivity (Y) is positive, meaning that the higher the level of technology adoption, the higher the productivity achieved by manufacturing companies.

This positive relationship aligns with economic theory and previous research findings that suggest the implementation of advanced technology, such as automation, artificial intelligence (AI), and the Internet of Things (IoT), can improve operational efficiency and reduce production time. With digitalization in manufacturing processes, companies can minimize human errors, optimize raw material usage, and increase production capacity without significantly increasing the workforce.

The significance implications of these findings are crucial in the manufacturing industry context. If the influence of technological innovation is proven to be significant and positive, investment in technology should be a top priority for manufacturing companies aiming to enhance their competitiveness. Additionally, the government and other stakeholders need to encourage technology adoption by providing incentives such as subsidies or workforce training to ensure that the benefits of technological innovation can be widely felt across all industrial sectors. However, for companies not yet prepared to adopt new technology, mitigation strategies are needed to ensure that the transition to technology-based systems does not disrupt operations. Therefore, understanding the significance and direction of technological innovation's impact on productivity can help formulate more effective policies to support the manufacturing industry's growth in the digital era.

The Influence of Control Variables on the Main Relationship:

Control variables in this study, such as company scale, workforce education level, and investment capital, play a crucial role in determining how effectively technological innovation enhances manufacturing industry productivity. Company scale is a key factor in technology adoption, with larger firms generally having more resources to implement advanced technology than small and medium enterprises (SMEs). With stronger infrastructure, large companies can better integrate automation, artificial intelligence (AI), and the Internet of Things (IoT) into their production processes, ultimately improving operational efficiency and competitiveness. Conversely, SMEs often face challenges in accessing technology due to high costs, a lack of experts, and limited investment capital.

Workforce education level also determines the success of technology adoption in the manufacturing industry. Employees with higher educational backgrounds tend to grasp and adapt to new technology faster, enabling companies to optimize its use. On the other hand, workers with lower education levels may struggle to adapt to technology-based systems, requiring additional training to bridge the skills gap. Therefore, companies looking to enhance productivity through technological innovation need to ensure that their workforce possesses the skills needed for a digital-based industry. Additionally, investment capital is a crucial factor in determining the extent to which technological innovation can be adopted and optimized. Companies with substantial investments in technology tend to experience higher productivity increases because they can access modern equipment, data-driven manufacturing systems, and employee training to support technology use. Conversely, companies with limited capital may struggle to adopt innovation, which can slow productivity growth. Thus, businesses need to consider the right investment strategy to ensure that technological innovation delivers maximum impact on their performance.

Managerial and Policy Implications:

These research findings have significant implications for company management, the workforce, and policymakers in promoting technology adoption to enhance manufacturing industry productivity. Companies must optimize their technology implementation strategy by ensuring that innovations such as digitalization, automation, and artificial intelligence (AI) align with production needs and workforce capacity. One strategic step is to integrate technology gradually, starting with the most efficiency-critical processes so that its impact can be measured before wider implementation.

From a policy perspective, the government plays a crucial role in accelerating technology adoption in the manufacturing sector through various incentives and regulations. Fiscal incentives, such as tax reductions for companies investing in Industry 4.0 technology, can encourage more aggressive technology adoption. With strong collaboration between industry and the government, technology adoption can be more effective in enhancing the competitiveness of the manufacturing industry at both national and global levels.

CONCLUSIONS

This study demonstrates that technological innovation has a significant impact on increasing productivity in the manufacturing industry. The results of linear regression analysis confirm that the adoption of technologies such as digitalization, automation, and artificial intelligence (AI) positively contributes to production efficiency, operational cost reduction, and increased company output. These findings align with previous studies emphasizing the importance of technology adoption in enhancing industrial competitiveness in the digital era. However, the impact of technological innovation on productivity is also influenced by various internal factors, such as workforce readiness, company scale, and the level of investment in technology. Although technological innovation has been proven to boost productivity, this study also identifies several challenges in its implementation, particularly for Micro, Small, and Medium Enterprises (MSMEs). High investment costs, infrastructure limitations, and a lack of skilled labor are the main obstacles to technology adoption. Therefore, a comprehensive strategy is needed from companies to optimize technology utilization and enhance workforce capacity through continuous training programs. Additionally, government support in the form of innovation-friendly regulations and fiscal incentives can accelerate digital transformation in the manufacturing sector. Policies that encourage investment in technology, digital infrastructure development, and the provision of technology-based training programs can help strengthen the competitiveness of the manufacturing industry at both national and global levels. With synergy between the industrial sector, the workforce, and the government, technological innovation can be optimally utilized to improve productivity and sustainability in the manufacturing industry in the future.

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